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Evaluation of two common vulnerability index calculation methods

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ABSTRACT

The potential benefits of using a geometric mean method for computing a vulnerability index are presented using both simulated variables as well as data from a Canadian coastal geodatabase (CanCoast). The assessment of vulnerability of natural and built coastal infrastructure to sea level rise is used to demonstrate the advantages of this method for climate change adaptation planning and decision-making. As with most real world datasets the probability distribution of individual variables in CanCoast may be skewed; this can significantly impact the resulting vulnerability index depending on the calculation method employed. The primary advantage of using a geometric mean is that the index output will remain within the original range and maintain the distributional characteristics of the input variables. This can reduce the need for subjective expert opinion in the process of assessing the vulnerability index. A comparison of the resulting computation using both the Gornitz (1991) method and the geometric mean is provided for the Atlantic Canada coastline.

1. Introduction

In the field of risk assessment, the term vulnerability has been broadly applied and equated to concepts such as resilience, marginality, susceptibility, adaptability, fragility, and risk (Liverman, 1990; IPCC, 2014a). It is an elusive term that continues to provide challenges in the consistency of its application (Timmerman, 1981; Fussel and Klein, 2006). Nonetheless, the concept continues to be used and has recently been described by the Intergovernmental Panel on Climate Change (IPCC, 2014b) as:

> "The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt."

In coastal assessment research, numerous indices have been devised to evaluate the vulnerability of a shoreline to the effects of climate change (Preston et al., 2011; Ramieri et al., 2011; Abuodha and Woodroffe, 2006.). Each index is a composite of multiple quantitative and qualitative indicators that, via some formula and weighting, delivers a single numerical result that is indicative of coastal vulnerability to a hazard (e.g. climate change). Regardless of the ambiguity surrounding the term and the various methods of assessing it, the primary purpose of a vulnerability assessment is to provide information that assists in decision-making and coastal adaptation planning (McLaughlin and Cooper, 2010; Smit and Wandel, 2006; Kelly and Adger, 2000). One of the early methods in this area of research that has been broadly adopted is the Gornitz (1991) Coastal Vulnerability Index (GVI) (Boruff et al., 2005; Pendleton et al., 2004; Thieler and Hammer-Klose, 2000; Shaw et al., 1998). The GVI method yields a vulnerability index for the coastline segments within study extents but does not accurately represent the frequency distribution or range of the input variables. As a result, researchers are then left to ordinate the index distribution into vulnerability categories (e.g. low, medium and high vulnerability) for graphical display (e.g. GIS output showing coastlines of varying degrees of vulnerability) using either expert opinion or by splitting the data into percentiles (Shaw et al., 1998).

Gibb et al. (1992) noted early on some deficiencies in using this calculation, including its tendency to distort the output range and distribution of the final index. Despite these known deficiencies, the GVI method is still commonly used in calculating a vulnerability index. In a search of published literature over the period 2014–2017, approximately 30% of the papers on coastal vulnerability used the GVI calculation for aggregating vulnerability variables (for example: Ferreira Silva et al., 2017; López Royo et al., 2016; Martínez-Graña et al., 2016; Tano et al., 2016).

In addition to the impact on data distribution, it should also be noted that Gornitz (1991) incorrectly describes GVI (Equation (1)) as the square root of the geometric mean:

$$\mathrm{GVI} = \sqrt{\frac{a_1 * a_2 * \ldots a_n}{n}} \tag{1}$$

The GVI is more accurately described as the square root of the

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product of the variables (a_i) divided by the number of variables (n) (or as it is sometimes described, the square root of the product mean). The true geometric mean (GM) is the nth root of the product of the variables ($a_1 - a_n$):

$$GM = \sqrt[n]{a_1 * a_2 * \ldots a_n} \quad (2)$$

Due to the prevalence of GVI in the current literature, this paper quantifies and compares the distributional impact of applying the GVI and the GM to both simulated input variables and an existing dataset of Canadian shoreline segments with environmental exposure variables (sea level rise, wind speed, wave height, coastal materials, and change in sea ice coverage). The importance of choosing an appropriate methodology when calculating vulnerability indices for climate change adaptation planning is discussed.

2. Methods and data

The following methodology will quantify and compare the distributional implications of the GVI and GM coastal vulnerability assessment methods using simulated variables. This will enable us to isolate the causes of observed differences in calculated vulnerability index distributions. Both indices will then be applied to actual coastal segment environmental variables to further demonstrate the "real-world" implications of assigning coastal vulnerability using different methods.

2.1. Simulated coastal segments

A model was written using R Statistical Software (R Core Team, 2016) to compare the resulting range and distribution characteristics for two vulnerability indices (GVI and GM). For a total of 1000 simulated coastal segments or data rows, scenarios using varying numbers of randomly generated coastal variables (3, 7, 10, 25, 50, 100 and 200) with means between 1 and 100 and a standard deviation of 1 were created. Using the R cut () function to divide the distribution into 5 equal parts, the distribution of each variable was recoded to a scale of 1–5, with 5 representing the most vulnerable and 1 representing the least vulnerable state. Each scenario was run a total of 30 times and the skewness, kurtosis, mean, median and range of the resulting coastal index distribution was captured for each run. The average for each distributional statistic for all runs was then calculated for each model scenario.

2.2. Application to a coastal dataset

The following is an applied example that compares the effects of using the GVI and the GM on CanCoast (Shaw et al., 1998), a Canadian coastal dataset. This dataset is a 1:50,000 scale dataset of the Canadian coast with updated values of five environmental/exposure variables. The variables used in this exercise are: predicted sea level change, wind speed, wave height, coastal materials, and change in sea ice coverage. The coastal materials dataset was already scored on an ordinal scale (1–5 based on increasing erodibility), but it was necessary to score the four other environmental datasets on an identical scale. The frequency distributions of each of these four coastline variables were tested for skewness and, if necessary, transformed prior to scoring so their distributions were approximately normal. Scoring of these four environmental variables was achieved by dividing each variable range into five equal intervals.

2.2.1. Sea level change

The regional projections of relative sea level (RSL) rise from the IPCC Assessment Report 5 (AR5) include effects of steric and dynamic changes, atmospheric loading, plus land ice, glacial isostatic adjustment (GIA), and terrestrial water sources (IPCC, 2013). The steric and dynamic changes were derived from 21 Atmosphere– Ocean General Circulation Models (AOGCMs) from the Coupled Model Intercomparison Project, Phase 5 (CMIP5). A 1-degree resolution grid of relative sea level change was calculated for all years between 2006 and 2100 for RCP4.5 and RCP8.5.

2.2.2. Wind speed and wave height

Modeled hindcasts of yearly maximum significant wave height (1990–2014) and maximum wind speed (1990–2012) were used. Both datasets were generated from IFREMER wave hindcasts using the WAVEWATCH III model with wind data from NCEP Climate Forecast System Reanalysis (CFSR) (Saha and Coauthors, 2010). Two high resolution (10 min) grids of Atlantic and Pacific maximum modeled wind speeds and maximum significant wave height were used for southern Canadian coastal areas while a coarser (30 min) worldwide grid was used for the Arctic areas. From these datasets maximum significant wave height over 25 years and maximum wind speed over 23 years were calculated.

2.2.3. Coastal materials

The base layers from which the coastal materials layer were derived were the Fulton surficial geology and the Wheeler bedrock geology, both at scales of 1:25 million (Wheeler et al., 1996). Where the surficial geology was greater in thickness than veneer, a score of 3–5 was assigned, with 5 being most erodible (muds, marine clay, materials that will flow) and three being less erodible (sands, gravels). Where there were surficial materials with a thickness of veneer or less, the bedrock geology was used as the basis for the score. Scores based on bedrock geology were assigned 2 if the geology was sedimentary, and 1 if igneous or metamorphic (Dr. Gavin Manson, Natural Resources Canada, Bedford Institute of Oceanography, Dartmouth, Nova Scotia, personal communication, 2015).

2.2.4. Change in sea ice coverage

Sea ice data from the Canadian Ice Service were acquired for each of the four regions (i.e. Atlantic, Eastern Arctic, Western Arctic and Hudson Bay), representing percent ice coverage for each week over four decades (1970s, 1980s, 1990, 2000s). For each region and decade, a single dataset was calculated to represent the sum of all weeks with ice coverage in excess of 50%, with a maximum possible score of 52 weeks for each decade. To measure change in ice coverage, the summary sheet from the 2000s was subtracted from the 1970s summary sheet. The final dataset represents the number of weeks of change in ice coverage greater than 50%. A positive number indicates a reduction in weeks of ice coverage, a negative number an increase in ice coverage.

2.2.5. Assignment of vulnerability scores to coastal variables

Variable values were categorized on a scale of 1–5 (low risk to high risk) (Table 1) by breaking the range into 5 equal divisions, except for Coastal material which were already categorized on a 1 to 5 scale in increasing erodibility.

3. Results

This section will provide an overview of the results using both simulated and real world data sets. The section with simulated variables will allow us to address the differences that result from the GVI and GM methods. The section using the CanCoast geodatabase will demonstrate the application of these approaches in Atlantic Canada.

3.1. GVI and GM comparison with simulated input variables

Using the simulated input variables as described in Section 2.1, calculations comparing the influence of the number of variables on the distributional output for both the GVI and the GM methods are provided in Table 2 and Fig. 1. The four key statistical measures chosen to

Table 1
Coastal variables with assigned risk.

	Low				High
	1	2	3	4	5
Sea level rise (m)	0.59 – ≤0.66	> 0.66 – ≤0.72	> 0.72 – ≤0.79	> 0.79 – ≤0.85	> 0.85 – ≤0.92
Windspeed (m/s)	20.8 – ≤23.0	> 23.0 – ≤25.1	> 25.1 – ≤27.2	> 27.2 – ≤29.3	> 29.3 – ≤31.4
Wave height (m)	1.8 – ≤3.5	> 3.5 – ≤5.2	> 5.2 – ≤6.9	> 6.9 – ≤8.6	> 8.6 – ≤10.3
Change in sea ice (weeks)	0.0 – ≤1.2	> 1.2 – ≤3.4	> 3.4 – ≤5.6	> 5.6 – ≤7.8	> 7.8 – ≤10.0
Coastal materials	1	2	3	4	5

Table 2
Gornitz vulnerability index (GVI) and geometric mean (GM) calculations for varying numbers of simulated parameters.

Number of variables	GVI calculations				GM calculations			
	Skewness	Kurtosis	Mean	Range	Skewness	Kurtosis	Mean	Range
3	0.22	2.99	2.90	1–5.4	−0.03	2.94	2.91	1.4–4.5
7	0.82	4.07	16.14	3.2–45.7	−0.02	2.96	2.87	1.8–3.9
10	1.13	5.09	67.81	9.9–243.5	−0.03	2.95	2.87	2.0–3.8
25	2.43	13.40	1.36E+05	7.0E+03–1.0E+06	−0.02	2.97	2.86	2.3–3.4
50	4.49	39.70	6.92E+10	9.6E+08–1.1E+12	−0.00	2.98	2.87	2.5–3.3
100	8.56	123.60	2.41E+22	4.5E+19–1.0E+24	−0.01	2.98	2.87	2.6–3.2
200	15.04	310.00	4.44E+45	3.9E+41–5.7E+47	−0.01	2.99	2.87	2.7–3.1

describe the results of the index calculation are: skewness, kurtosis, mean and range, where range refers to the upper and lower bounds of the computed index.

As expected, all four statistical measures increase as the number of variables increases in the GVI calculation. Skewness, a measure of the asymmetry of the data around the sample mean, is positive for a distribution in which the data are spread out more to the right. As is evident from Table 1, all GVI results are right-skewed and increase almost linearly with the number of variables. The kurtosis of a normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3. As is apparent from Fig. 1, the relationship between kurtosis and number of variables in the GVI computation is non-linear. In addition to the skewness and kurtosis increasing dramatically, the variation of these variables also increases substantially (Fig. 1). Both the mean and the range of the calculated GVI increase dramatically with increasing variable numbers and quickly fall far outside the range of the input values. The resulting outputs from the GVI calculation to simulated inputs brings into question how a practitioner evaluating coastal vulnerability could objectively assess this index.

In contrast to the GVI, the output of the GM calculation maintains a normal distribution with similar skewness and kurtosis regardless of the number of input variables (Table 1 and Fig. 1). Unlike the mean of the simulated GVI output, the mean of the distribution from the GM calculations (regardless of the number of input variables) is within the range of the input variables (1–5). The distributional range of the

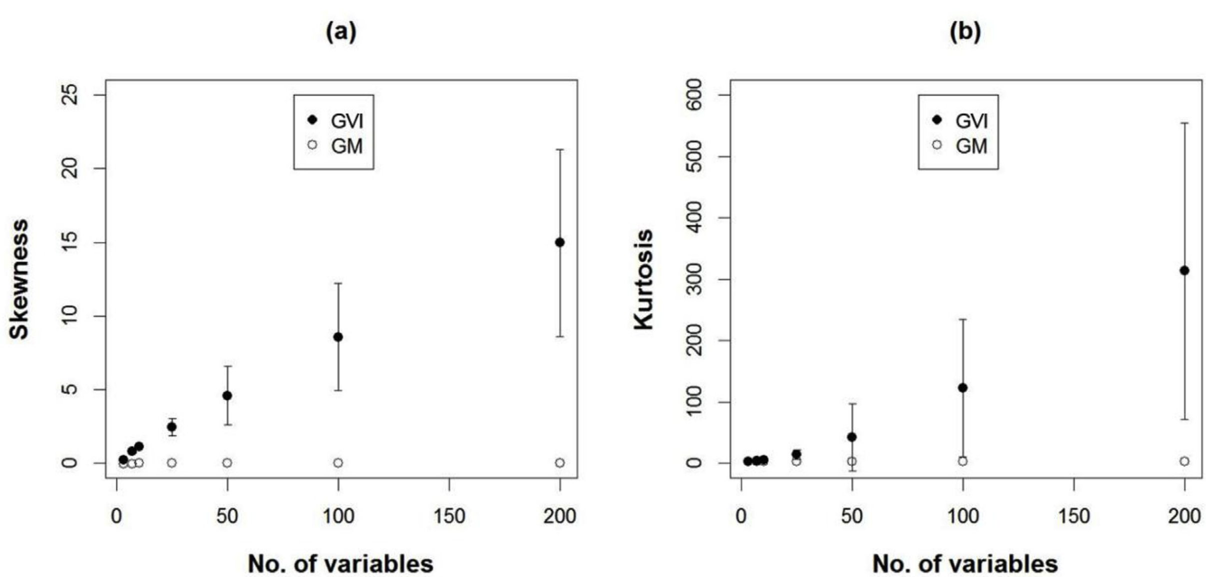

Fig. 1. Changes in a) skewness and b) kurtosis for GVI and GM calculations with increasing variable numbers. Error bars are plus/minus one standard deviation. Error bars on the GM datapoints are too small to appear at this scale.

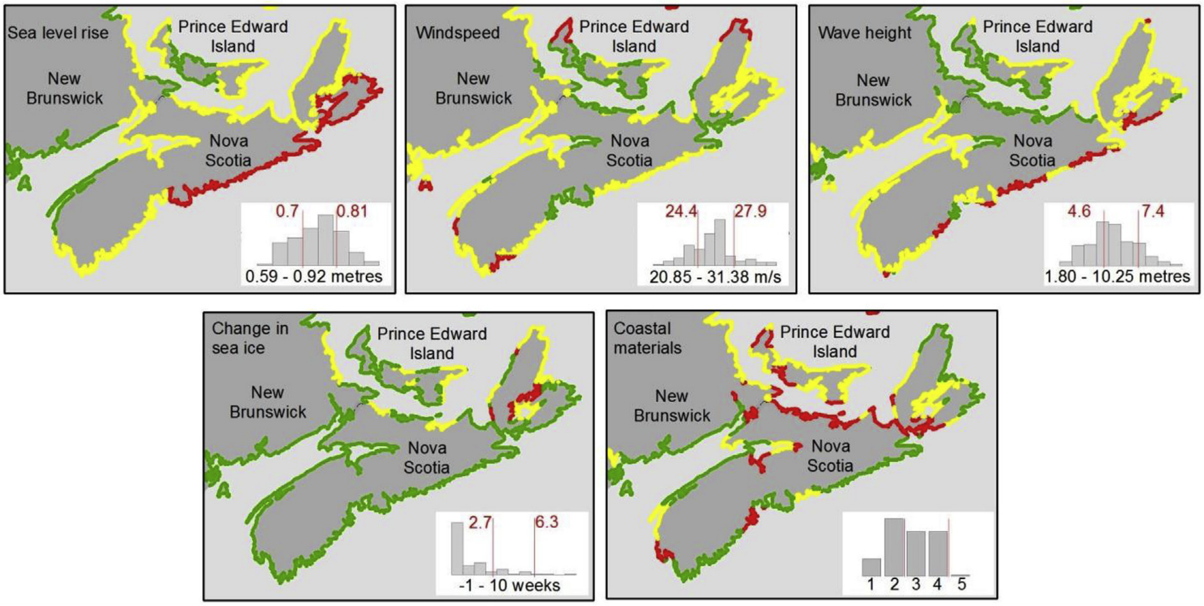

Fig. 2. Canadian maritime coastline with environmental variables.

simulated index calculation using the GM method shrinks with increased variable number, but the overall shape of the distribution and the standard deviation around the mean are similar to the distributional parameters of the input variables. Therefore, even though the range compression is a deficiency of the GM it is much easier to deal with than the combination of issues that result from using the GVI method.

3.2. GVI and GM comparison with real-world coastal environmental variables

Using the coastal dataset outlined in Section 2.2, both the GVI and GM methods were applied to the Canadian coastline. Given the broad scale of this coastline, the analysis in this section will focus on the southern region of Atlantic Canada (Fig. 2). An assessment of the GM index calculated for the coastal segments with the five variables is found to remain within the range of the input variables (1.25–3.81) and maintains a similar distributional shape to the input variables. Cutting the GM index distribution into 3 equal parts (low, medium and high vulnerability) reveals ranges and percentages that are substantially different from the results of the GVI calculation (Fig. 3) (Three vulnerability classes were used in this example to make the resultant maps less complex. In more complex vulnerability analyses a researcher may want to use more categories). It is evident that the GVI skewness results in a substantially higher proportion of the coastal segments being assessed as low vulnerability.

The major geographical differences between the two calculations appear on the north shore of Prince Edward Island (PEI) (Area 1), along the Nova Scotia and New Brunswick shores of the Northumberland Strait (Area 2) and in the Atlantic coastal region of Nova Scotia (Area 3). The north shore of PEI and the coastlines along the Northumberland Strait are comprised of sandstone and unconsolidated sand and are highly erodible (Forbes et al., 2004). Much of the Atlantic coast of Nova Scotia is dominated by the old and generally very hard rocks of the Meguma Group (Davis and Browne, 1996) and, hence, not readily erodible but sea level rise is expected to be high along that coast (up to 0.92 m by 2100 under RCP8.5). Wave heights and wind speed are also significantly higher along the Atlantic coast than in the more protected Northumberland Strait. In this region of Atlantic Canada, the GM calculation of a vulnerability index is more reflective of what is understood of the coastal environment and results in a more accurate assessment of vulnerability when compared to the GVI method.

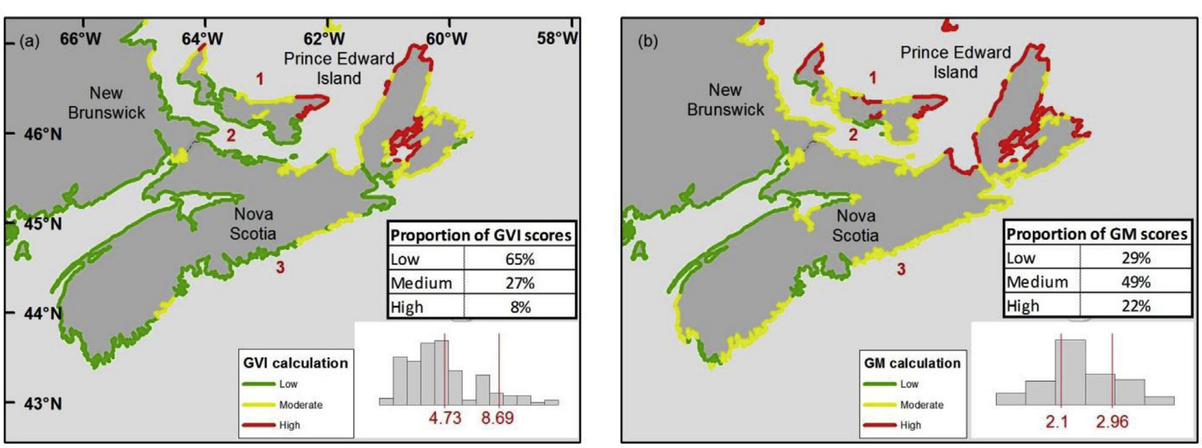

Fig. 3. Canadian maritime coastline vulnerability/risk scores as calculated using a) Gornitz (1991) GVI, and b) geometric mean. The resultant distributions were cut into three equal divisions.

4. Discussion

In choosing a specific method for the integration of variables in calculating a vulnerability index it is important to understand the effect a calculation will have upon the resultant index and its distribution. However, it is also important to understand the limitations of the data sets used in assessments, since these data sets are often incomplete or of limited accuracy and may compromise the reliability of vulnerability index calculations.

As expected, the GVI equation proposed by Gornitz (1991) is sensitive to the number of variables used; more variables increase the skewness, kurtosis, mean, and range of the coastline index distribution at predictable rates. While most researchers would not use more than seven variables, the distributional distortion even up to seven variables is substantial (Table 2). Transforming the resulting skewed index distribution to vulnerability categories is often a matter of expert opinion or arbitrary conversion to percentiles that split the distribution into different categories based on the frequency of the data values (e.g. n groups of similar frequency), as shown in the results section when applying the GVI and GM calculation to the coastal dataset (Fig. 3). This method of re-classification applied to skewed data is not an accurate reclassification of the distributional shape of the input variables and this can lead to a biased frequency of vulnerability categories that is not reflective of reality. The percentile method of reclassification assumes that each risk category is equally represented, when in fact it is clear that it is far more likely to see a moderate vulnerability category than an extreme one when the coastline index distribution is normal. The pitfalls of re-classification by expert opinion are more difficult to quantify as they will vary from study to study, but by categorizing based on some unknown criteria, invariably the distribution of the output will not reflect the input variables. Even if the distribution of the GVI is re-classified to categories with a distribution that roughly matches the input variable distribution (e.g. strongly right skewed to normal), the process of re-classification is unnecessary when other equations exist that result in vulnerability indices with distributions and ranges more reflective of their input variables. When the vulnerability categories (e.g. 1–5) are applied using the GM method, they more accurately represent the underlying data than the GVI.

Researchers using the Gornitz method inadvertently create a coastline vulnerability distribution that requires an arbitrary transformation to make the output interpretable. For instances in the literature where it might be useful to visualize the GVI as GM, there is a direct mathematical relationship between the two methods. Using Equations (1) and (2), the following relationship between the GM and GVI can be derived:

$$GM = \sqrt[n]{GVI^2 * n} \tag{3}$$

As shown in Table 2, the advantage of using the geometric mean is that the index output is within the range and distributional characteristics of the input variables. As well, it is resilient to variables with extreme values that may disproportionately impact index output (Huang et al., 2012; Clark-Carter, 2005). Nonetheless, the index is not without its drawbacks. As shown in Table 2, as more variables are added, the range of the resulting index distribution decreases. However, by breaking the distribution into equal bins instead of quantile breaks one can use the decreased range in the same way as the input variables. Even as more variables are added, the shape of the distribution does not change, only the range. The output of the geometric mean shows (as does Shaw et al., 1998) that input variables were right skewed and impacted the distribution of the final index. As with the calculation of the Human Development index (UNDP, 2011), it is recommended that the input variables are transformed to be approximately normal in distribution prior to calculating the final index. This reduces the bias associated with the effect of combinations of similarly skewed variables that could influence the distribution of the index calculations of coastal segments as was observed in Shaw et al. (1998).

Cooper and McLaughlin (1998) underscore an important point that "there is no single index that can provide an assessment of risk from all potential environmental perturbations". This continues to be true today, as many older methods to assess coastal vulnerability have been adapted and modified for modern approaches (Ramieri et al., 2011; Fussel and Klein, 2006). Additionally, most methods of vulnerability assessment are tools to highlight the relative vulnerability of one section to another (in this case, sections of coastline) and are not finely-tuned enough to show absolute vulnerability. Nonetheless, the broad application of the GVI method seems unnecessarily complicated based on the evidence provided and would not be recommended in light of the statistical evidence of output distortion and lack of mathematical justification. It is recommended that other approaches be investigated as alternatives to avoid misinterpretation of the level of coastal vulnerability to various coastal stressors.

5. Conclusion

Sea level rise associated with global climate change poses a significant threat to coastal communities, both in terms of natural and built infrastructure. In order to decrease bias in science advice provided for decision-making and policy development for coastal management, it is necessary to reduce the need for subjective expert opinion in the computation of vulnerability indices. As summarized by Nguyen et al. (2016), there are many approaches to assessing coastal vulnerability and the complexity of this process results in outcomes that make it difficult to compare studies.

The geometric mean has the potential to improve the approach to calculating a vulnerability index through improved preservation of the original statistical characteristics of the data throughout the assessment process. There are some limitations of the geometric mean, such as the tendency to compress the output range with the increasing number of variables; however, these issues can be addressed with objective mathematical procedures and do not require intervention of expert opinion. Of course, the input of subject matter experts should not be eliminated from the process of assessing coastal vulnerability, but this should be limited to aspects for which rigorous mathematical or statistical methods are not able to address the questions posed.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.ocecoaman.2018.03.041.

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